Tampereen yliopisto

Saara Rautiainen

IMPLEMENTING PERSONALIZED PRODUCT RECOMMENDATIONS: A CASE STUDY ON POWER FINLAND

Faculty of Information Technology and Communication Sciences
Master's Thesis
May 2023

TIIVISTELMÄ

Saara Rautiainen: Implementing personalized product recommendations: A case study for Power Finland
Pro Gradu tutkielma
Tampereen yliopisto
Tietojenkäsittelytieteiden tutkinto-ohjelma
Toukokuu 2023

Kaupankäynti ja kulutus ovat siirtyneet tämän vuosituhannen aikana yhä voimakkaammin verkkoon, ja verkkokaupan kehitystyöstä on muodostunut tärkeä osa yrityksen liiketoimintastrategiaa. Verkkokauppa on käytännöllisen luonteensa vuoksi kuluttajien suosiossa, ja se tarjoaa myös yrityksille uusia mahdollisuuksia kohdeyleisön tavoittamiseen, kuten personoinnin. Konseptina personointi ei ole uusi, mutta verkkokaupan tarjoamat käyttötarkoitukset ovat muokanneet siitä entistä toimivamman. Tämä kehitys on kuitenkin tuonut ilmi myös personoinnin mahdollisia haittapuolia, kuten kuluttajien huolen tietoturvasta.

Tutkielman tarkoitus on kokonaisvaltaisesti kartoittaa personoinnin toteutukseen liittyviä mahdollisuuksia ja uhkia sekä selvittää, vaikuttaako personoinnin käyttöönotto merkittävästi Power Finlandin keskeisiin suorituskykymittareihin verkkokaupassa. Tutkimus tarkastelee personointia verkkokauppakontekstissa selvittämällä ensin personoinnin implementointiin liittyviä käytännön käsitteitä. Tämän jälkeen tutkimus etenee kuluttajan ja yrityksen väliseen vuorovaikutukseen, sekä kuluttajan kognitioon digitaalisessa ympäristössä. Teoreettinen tausta käsittää myös kolme tapaustutkimusta, jotka havainnollistavat personoinnin käyttöönottoa kolmessa samalla toimialla toimivassa yrityksessä.

Tutkimuskysymyksiin vastaamiseksi toteutettiin aineiston pohjalta SWOT-analyysi sekä A/B-testi, joka vertasi Powerin olemassa olevaa tuotesuosituskarusellia tutkimusta varten toteutettuun personoituun karuselliin. A/B-testi ei antanut tilastollisesti merkittävää tulosta personoinnin toimivuudesta tuotesuosituskarusellissa. SWOT-analyysissa esille tulleet huomiot osoittivat personoinnin kuitenkin olevan yhteensopiva Powerin liiketoimintastrategian kanssa. SWOT-analyysi toi esiin erityisesti MyPowerin ja personoinnin positiivisen vaikutuksen toisiinsa sekä mahdollisuuden luoda kokonaisvaltaisempia asiakassuhteita personoinnin kehityksen avulla.

Avainsanat: e-commerce, personointi, verkkokauppa

ABSTRACT

Saara Rautiainen: Implementing personalized product recommendations: A case study for Power Finland
Master's Thesis
University of Tampere
Master's Degree in Computing Sciences, Human-Technology Interaction
May 2023

Over the last decade, online shopping has grown in popularity among consumers due to its convenience and efficiency and has made the development of e-commerce an indispensable part of companies' business strategies. It also provides businesses with new ways to address their target audience, such as personalization. While the field of marketing research has long recognized the advantages of personalized content in advertising and commerce, there are a plethora of additional variables to consider when personalization is integrated into digital platforms. There exist public apprehensions on the topic and experts have raised words of caution indicating that the implementation of automated personalization in a digital context needs careful consideration of additional variables and potential threats.

The purpose of this thesis is to comprehensively map the opportunities and threats related to the implementation of personalization and to determine whether the introduction of a web store personalization feature significantly affects Power Finland's key performance indicators. The study examines personalization in the context of e-commerce by first exploring practical concepts related to its implementation. The literature review then proceeds to the interaction between the consumer and the company, as well as the consumer's cognition in the digital environment. The theoretical background also includes three case studies that illustrate the implementation of personalization in three companies operating in the same industry.

To answer the research questions, a SWOT analysis based on the data and an A/B test comparing Power's existing product recommendation carousel to a personalized carousel were conducted. The A/B test did not provide statistically significant results regarding the effectiveness of personalization in the product recommendation carousel. However, the observations made in the SWOT analysis showed that personalization is compatible with Power's business strategy. The SWOT analysis highlighted in particular the positive impact of MyPower and personalization on each other and the possibility of creating more comprehensive customer relationships through the development of personalization.

Keywords: e-commerce, personalization, online shopping
The originality of this publication has been verified with Turnitin OriginalityCheck.

1 Introduction

Due to the multitude of retailers shifting their focus on e-commerce to keep up with the digital transformation of the 21st century, competition for customers is fierce and companies are increasingly investing in providing their customers with personalized content and services. According to Instone, personalization refers to user and content profiles being matched according to a specific set of rules (2004). This distinction holds in the field of e-commerce, where "personalization is about building customer loyalty by building a meaningful one-to-one relationship; by understanding the needs of each individual and helping satisfy a goal that efficiently and knowledgeably addresses each individual's need in a given context" (Riecken, 2000).

The rapid advancement of technology has presented businesses with more tools for providing their customers with real-time personalization and apart from promising to improve customer experience, personalization in e-commerce is also regarded as a powerful way to increase sales (Gregg et al., 2016; Ariker et al., 2015). The application of product and content personalization has been a driving force for companies such as Amazon (Ho, 2006) and Spotify (Hracs & Webster, 2021), and an increasing number of companies are investing more in either their marketing and development teams or third parties to reap the promised benefits of personalization – providing their customers with value and increasing the company's conversion and retention rates.

As our relationship with technology evolves, so does our relationship with commerce. The ease and convenience provided by online retail has turned many to prefer it over traditional brick-and-mortar stores, and many customers are expecting an experience out of the ordinary "one-size-fits-all"- approach. Accenture reports that "91% of consumers are more likely to shop with brands who recognize, remember, and provide relevant offers and recommendations" (Accenture Interactive, 2018), indicating that not jumping on the personalization bandwagon can potentially be detrimental to business. The necessity of implementing personalization in e-commerce suggests a paradigm shift in how we treat and view online shopping today, shifting its purpose from being a means to an end, to providing an experience unique to each customer. This suggests the significance of research on the subject in the field of digital marketing as well as Human-Technology Interaction.

However, personalization has brought forth some criticism and concern among researchers due to its reliance on the large-scale use of customer data and potentially intrusive marketing tactics. Sunikka and Bragge state the importance of further studies regarding consumers' views and drawbacks on the topic of content personalization (2008), and Ariker et al. (2015) bring forth the potential of digital personalization coming off as off-putting to certain customers. Furthermore, the perceived prevalence of data breaches has made data privacy a growing concern. Therefore, in a time when consumers are becoming increasingly more aware of their relationship with technology, delving into deploying personalized content in e-commerce should be approached with care (Sunikka & Bragge, 2008).

The motivation behind this thesis on content personalization stems from its apparent indispensability in today's competitive economy, and the juxtaposition of customers' anxieties around data between their expectations to be provided streamlined shopping experiences. This thesis work is done in collaboration with Power Finland, to improve the performance of Power's personalized marketing content. Power Finland is a home electronics retailer owned by Power International, which owns and operates stores and online shops in Norway, Denmark, Sweden, and Finland. Power International aims to provide customers with affordable electronics with an emphasis on great customer experience. The following research questions are formulated to map the opportunities and potential pitfalls of implementing a data-driven, automated approach to personalized product recommendations and to test how automated content fares against manually created content.

RQ1: What are the opportunities and threats of implementing automated personalized marketing content in the context of e-commerce?
RQ2: Are automated personalized product recommendations more effective than Power's current product recommendations?

To answer the first research question, a SWOT analysis (Schooley, 2022) is conducted based on findings from related work and case studies to address notions that should be taken into consideration during the development process. The second research question is addressed by implementing a minimum viable product (MVP) product recommendation carousel with automated personalized content, and by testing the feature with A/B testing to see the effects it has on revenue, transactions and bounces.

2 Theoretical Background and Related Work

The theoretical framework of the study consists of three core concepts: Personalization in e-commerce, marketing automation, and recommender systems. These focal concepts and their relationships are depicted in Figure 1.

The conducted literature review begins by presenting an overview of personalization in an e-commerce context by examining value creation (Chapter 2.2), the effects on customer cognition (Chapter 2.3) and the information privacy paradox theory present in personalization studies (Chapter 2.4). After providing a background for e-commerce personalization through a business and Human-Technology Interaction perspective, the literature review moves on to discuss the some of the common methods of technical implementation of personalization.

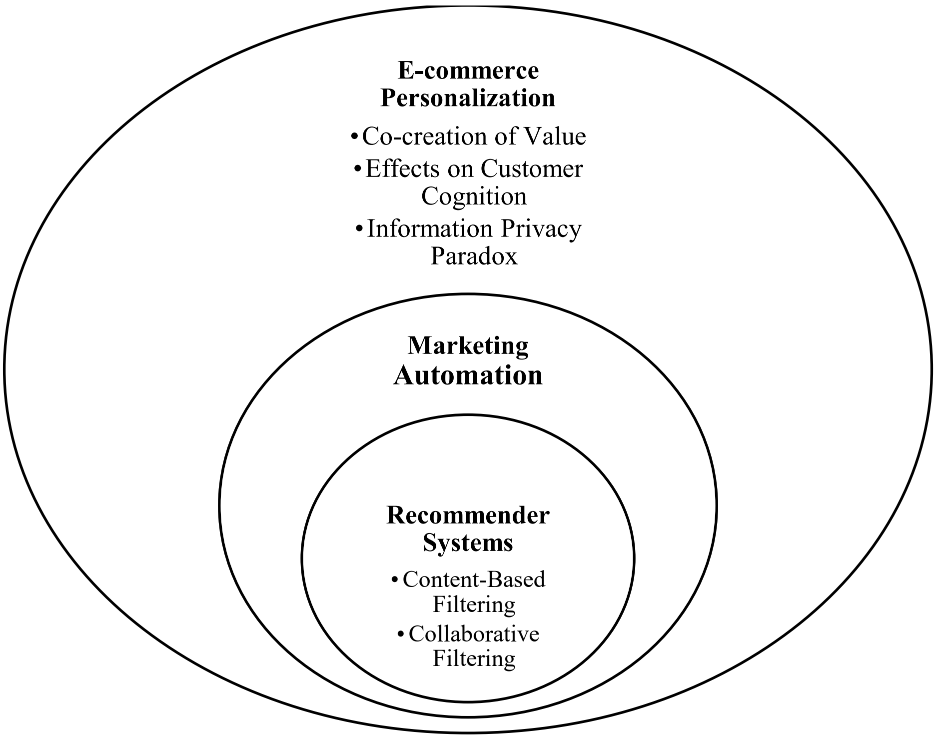


Figure 1. Theoretical Framework.

2.1 Personalization from an e-commerce perspective

Fan and Poole distinguish six different areas of study of personalization: "marketing/e-commerce; computer science/cognitive science; architecture/ environmental psychology; information science; and social sciences including sociology, anthropology, and communication" (Fan & Poole, 2006). As personalization is an umbrella term utilized through multiple fields and implementation techniques (the largest dimension in Figure 1), a proper distinction as to what commercial personalization is, should be made. As stated earlier, personalization involves the matching of user and content profiles according to a specific set of rules. In e-commerce, these rules will often be a combination of business requirements, such as the intent to sell more high-margin products, and implicit or explicit user requirements (Instone, 2004). Despite the vast body of literature on commercial personalization, research conducted on personalization before the emergence of digital marketing technologies does not directly apply to personalization in today's commercial environment, as interpersonal interaction in retail has been significantly reduced (Park, 2003), and information can be communicated to customers through multiple mediums, all of which have their unique affordances.

Furthermore, marketing strategies can also be automated to a large extent, and the large amount of consumer data available has forever changed how this information can be utilized in commerce. The data to create personalization rules and algorithms is sourced from user profiles, which can be either explicit, such as brands that the customer has manually indicated that they are interested in, or implicit, such as data gathered from user clicks on the online stores website (Instone, 2004). The rising popularity of e-commerce mobile applications also enables the collection of various location-based data points. By analysing the created data, the right information can be delivered to the right customer, at the right time (Park, 2003; Tam, 2006). It must be noted, however, that the relevance of the content is dependent on the amount of data points available and how much of their personal data customers are willing to give out to the organization.

Commercial personalization is specifically distinguished by its aim of generating sales opportunities (Ho, 2006) and increasing customer loyalty and supporting brand building (Riecken, 2000). The short-term goal of personalization is to provide the customer with more relevant and useful content, such as product recommendations, to improve customer experience, whereas the long-term goal of personalization is to generate more business opportunities (Ho, 2006). Personalization in e-commerce can also be harnessed to diminish information processing efforts to positively influence purchase intention (Dzulfikara, ym., 2018) and is mainly focused on the content of the system (Fan & Poole, 2006).

The implementation of these systems requires thorough research on customer profiles and meticulously carried out market segmentation. Customer needs often have stark contradictions with businesses' goals, indicating that these two must be treated as separate entities. The goals of a frugal consumer who is apprehensive about disclosing their data do not align with those of a business trying to maximize their profits. However, successful commercial personalization cannot be carried out without both parties benefiting (Fan & Poole, 2006). Therefore, the features of commercial personalization should ideally be geared towards marketing tactics proven to boost both revenue and customer satisfaction.

Commercial personalization systems are structured according to specific business needs and marketing strategies. During the design process, the three dimensions of personalization should be addressed: what is personalized, the target of the personalization and who does the personalization (Fan & Poole, 2006). The personalized variable in e-commerce can be any customer touchpoint, such as marketing newsletters or the user interface of the online store. The target dimension is divided into two parts, individuated and categorical targets. When personalization is categorical it seeks to reach entire market segments, whereas individuated categorization targets only one person uniquely based on their shopping behaviours. Whether personalization is implicit or explicit depends on the personalizing agent; when a customer is offered a choice to personalize the system or delivered content themselves, it is implicit. However, when personalization is carried out by the system, it is considered explicit. Explicit content personalization can follow traditional market research methods, but personalization delivered by marketing automation is regarded as a preferred method in today's fast-paced and competitive commercial environment.

After the overview of digital personalization in an e-commerce context, the following segments will discuss the implications personalization has regarding customers and businesses. These implications are based on pivotal branches of research related to digital personalization, as noted by Oberoi et al. (2017). They divide the existing literature on web personalization into three categories: the benefits it brings to the business, the effects on customer cognition and the implications on consumer privacy.

2.2 Co-Creation of Value Through Personalization

A key requirement for the success of businesses is being able to foster strong customer relationships, which can be achieved by meeting customer needs accurately. Ball et al. conclude in their study that personalization is a precursor for customer satisfaction and trust, which in turn influence brand loyalty. They also found that personalization compensates for a clear brand image, as individual trust surpasses the reliance on the collective perception of a brand or product (2003). In other words, creating a sense of exclusivity through personalized marketing lets organizations foster a one-on-one relationship with customers that enhances the individual's perception of the organization, which can compensate for a weaker brand image. These improved customer relationships translate directly to customer retention as a significant benefit for businesses (Ranaweera & Prabhu, 2003).

Personalization also has the potential to reduce acquisition costs by up to 50%, lift revenues from 5% to up to 15%, and increase the effectiveness of capital spent on marketing by 10% to 30% (Gregg et al., 2016). Moreover, Parkes (2001) states that e-commerce websites that utilize personalization technologies have been told to gain annual revenue increases of up to 52% and according to Ariker et al. (2015), sales have the potential to increase by 10 percent or more as a consequence of personalized marketing, as well as deliver a five to eight times higher return on investment on average (Parkes, 2001; Ariker et al., 2015).

Statistics show that correctly utilized personalization can provide significant monetary value for an organization. However, as stated earlier, for businesses to be able to reap the benefits of implementing personalization systems, there must exist a valid value proposition presented to the user, as value is only created in collaboration with the customer (Ordanini & Parasuraman, 2011). Therefore, the time and effort allocated for the employment of personalized systems such as newsletters, product recommendation banners or offers, must be carried out with consideration for the customer's best interest. Babet makes a distinction in his research with the terms "personalization" and "targeting", claiming that personalization is the process of delivering targeted solutions to a customer, whereas targeting is the act of advertising a specific product or service to a customer based on their preferences or traits used in customer profiling (Babet, 2020). The fine distinction demonstrates the customer-centric nature of personalization and how personalization should be carried out by basing targeting decisions on customer created data.

Examples of personalization features that can deliver tangible benefits to customers can be seen in Figure 2, where Dzulfikara et al. differentiate distinct features of commercial personalization used in today's e-commerce environment based on an extensive literature review (2018). The relationship these features have with value creation for both parties can be observed in the diagram presented in Figure 3, which is based on the framework of personalized marketing created by Vesanen (2007). It highlights how the benefits are generated to the customer through relation and interaction with the marketer via marketing outputs. The various possible commercial personalization features are centred, but the emphasis is on the execution space encompassing both the customer and marketer as well as the product of personalization. This is the space in which the results of personalization are generated. Benefits for the customer include better product matches, better service, and more streamlined communication (Vesanen, 2007). In addition, when implemented successfully, content personalization can provide customers with convenience due to reduced search time and satisfaction, both of which consumers hold in high regard (Ball et al., 2003; Zhu et al., 2017)

Commercial Personalization Features	**Description**
Rewards	An offer presented to the customer based on their purchase habits or loyalty.
Online Advertisement	An advertisement on the company's website or paid ads outside of it, that adjusts the content based on user preferences or behaviour.
Pricing	Personalized pricing of products that is based on a users behaviour, categorisation or preferences.

Promotions	A feature that promotes products to a user based on user behaviour or preferences
Discount	Personalization of discounted prices for individual users based on behaviour or preferences.

Figure 2. Features of commercial personalization (Dzulfikara, et al., 2018).

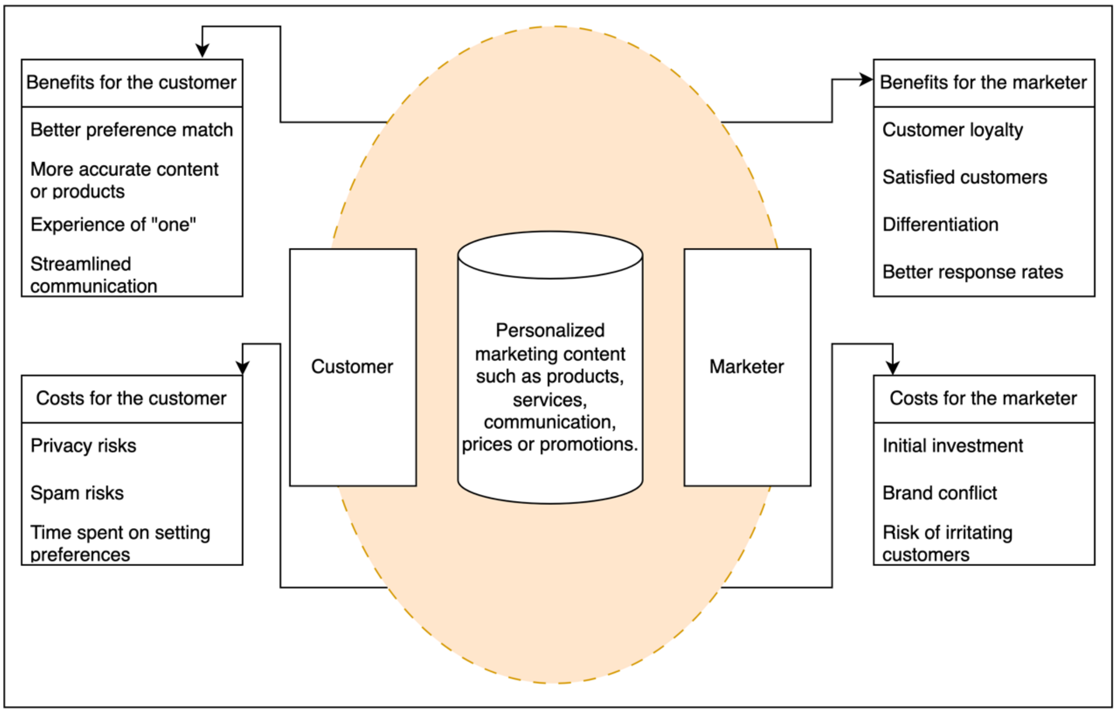


Figure 3. Framework of personalization.

Despite an abundance of data on the appeal of personalization to both customers and businesses, the case for commercial personalization should also be addressed through the effects on customer cognition, as this makes up a large part on how the value propositions of the company are perceived, and how effective they are in predicting purchase probability as well as customer retention. For instance, receiving personalized messages from businesses' communication channels can increase the social presence recognized by customers, which in turn leads to trust. Trust has been proposed to be a high predictor of purchase intention along with familiarity (Gefen & Straud, 2004). The process of trust creation, however, is multi-dimensional and dependent on an array of independent variables, such as integrity, predictability, and the trusting disposition of the individual (Gefen & Straud, 2004). The context-dependent nature of the perception of personalization efforts calls for a review of how personalized information is processed.

2.3 Effects on Customer Cognition

Consumer's choice is based on our systems of decision making and information processing, as well as the attributes of the decision-making environment (Huber & Seiser, 2001). In their seminal work, Tam and Ho (2006) discuss the effectiveness of web personalization through the lens of social cognition research. When met with attention provoking stimuli, a human will go through the process of cognitive processing by encoding and organizing the received data through related prior experiences and pre-existing schemas. This information is retrieved from the permanent to the working memory, and any schemas updated by the information processing will be again stored back in the permanent memory (see Figure 4). It is argued that self-referencing information, meaning information addressing a person directly, is stored more vividly in the permanent memory and better recalled as it is compared against an already highly organized schema, the self (Tam, 2006; Debevec & Romeo, 1992). The self-schema is most responsible for inferencing and judgment of stimuli, and is comprised of beliefs of oneself, influencing a person's perception of the surrounding world (APA Dictionary of Psychology, 2022).

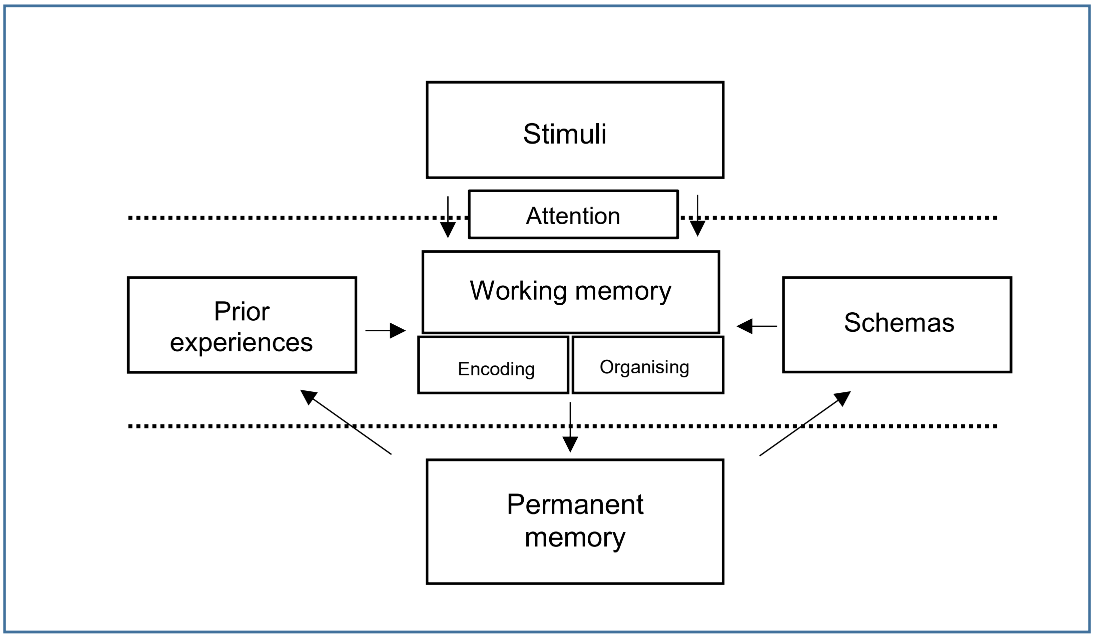


Figure 4. Effects on customer cognition.

Research has shown that the persuasiveness of a message is increased when it addresses the observer's image of themselves, and that more effort will be allocated into reading advertisements with self-referent information (Wheeler et al., 2005). Moreover, there is evidence that commercial communication matching a person's self-schema can positively contribute to attitude change (Wheeler et al., 2005), and attitude towards personalization is also argued to be a key indicator of the level of persuasiveness and an influencing factor towards behavioural intention (Park, 2003).

However, the self-schema itself is not an immutable entity and there are many other context-dependent variables at play during information processing that shape behavioural intention, which in the context of e-commerce can be referred to as intent to purchase. The intent to purchase can also be affected by how alternatives of the product or service are framed, trust in the product or service, and the user interface the user is presented with (Tam, 2006). Therefore, the design of web personalization systems should both account for the importance and fluidity of the self-schema and be able to address variables influencing intent to purchase.

In addition, for web personalization information to be effectively processed, the content must be relevant for the user's processing goals. A processing goal in the context of e-commerce can refer to e.g., making a purchasing decision or wishing to engage in idle browsing. In their study, Tam and Ho discovered that when met with relevant content that matched their processing goals, the users would spend less time on decision making and seek less additional information. This is due to people being more sensitive to stimuli that is relevant to what they are currently cognitively engaged with. The acceptance and evaluation of relevant information was also higher, as it was also for self-referent content (Tam, 2006). Interestingly, this context-specificity applies also to how the appeal to similarity is perceived. O'Keefe notes that the effects that similarities presented in communication have on the perceived credibility and trustworthiness of the communicator are affected by how relevant the similarity is to the issue at hand (O'Keefe, 2002).

Moreover, the manner and frequency in which personalized content is delivered plays a role in how it is processed. As an example, Tintarev and Masthoff stipulate the importance of explanation messages that accompany personalized content to increase transparency and therefore user trust in the system. Kisielus and Sternthal on the other hand suggest that a mixture of image and text has yielded better persuasive results, hypothesized to be due to information being processed through various pathways and subsequently leading to more effective cognitive processing (Kisielius & Sternthal, 1984). Intriguingly, the overuse of self-referent messaging can in turn have a negative effect on the persuasiveness of personalized content as oversaturation can interfere with the processing of the original message (Tam, 2006). The effect bears resemblance to the "uncanny valley" phenomenon, in which intelligent agents are perceived to be eerie when their appearance of behavior feels too familiar. Similarly, the overuse of self-referent information can potentially be perceived as too familiar, eerie, or intrusive. Intrusiveness can also be a pitfall in creating explanations for personalization utilizing demographic data as Tintarev and Masthoff illustrate: "anecdotally we can imagine that many users would not want to be recommended an item based on their gender, age, or ethnicity (e.g., "We recommend you the movie Sex in the City because you are a female aged 20-40.")" (Tintarev & Masthoff, 2011, s. 505).

However, reliance on merely making personalized content easy to process is not enough to create value for both business and customer. As personalization systems require customer data to be successful, providing customers with personalized content would necessitate an incentive to be presented to them based on which they would be willing to give out personal information. Today, the average consumer is more aware than ever of the potential repercussions of allowing personal information to be gathered in the interest of commercial perks. Nonetheless, consumers expect streamlined shopping services and relevant marketing, which is why the stream of literature discussing the privacy paradox is making headway.

2.4 Information Privacy Paradox

Today's digitalized consumer culture has brought forth an intriguing contradiction regarding consumers' attitudes towards personalization and the use of their data. The paradox noted in academic literature regarding consumers' data privacy apprehensions and a simultaneous willingness to receive more relevant and personalized content in an e-commerce context is called the information privacy paradox (Kokolakis, 2015). Recent studies and surveys demonstrate that individuals exhibit a significant unease about the use and collection of their personal data (Kokolakis, 2015). For example, an Accenture study discovered that around 70% of consumers are apprehensive about data privacy and the use of self-generated data in commerce (Accenture, 2020).

On the other hand, a study on the subject by Carrascal et al. (2013) found individuals to value their browsing history at the low price of around 7 euros, whereas their most "valuable" data related to offline information such as age and address, was valued also at quite a low price of 25 euros. Furthermore, another study by Accenture found that about 83% of consumers have no objection to sharing their data in exchange for a better shopping experience (Accenture Interactive, 2018). The numbers suggest an incentive to dig deeper into the reasons of this contradiction, and how the negative connotations of personalization can be mitigated while simultaneously providing customers with the streamlined experience they expect.

One of the early studies on the phenomenon conducted by Norberg et al. found out that individuals disclose a considerably larger amount of personal data than their stated intentions indicate (Norberg et al., 2007). The study consisted of a sample of students being surveyed about their willingness to give out certain information and later having questions regarding the same information asked from them by a market researcher, proving their hypothesis that privacy concerns and intention do not align with actual behaviour. Evidence therefore illustrates that a person's abilities to efficiently assess privacy risks and consistently align behaviour to intention are rather weak.

The findings of Norberg et al. relate to peoples' perception of the privacy trade-off. When individuals are making decisions concerning their willingness to give out their data in digital settings, they go through the process of cost-benefit evaluation to determine whether the trade-off is beneficial for them, to the best of their abilities. The evaluation process measuring the expected benefits and costs of a decision is called the subjective expected utility (SEU) (Gouthier et al., 2021). In the context of e-commerce, the SEU is comprised of the customers insights of what the company can provide to them and how that fares up against potential privacy breaches or data misuse. Consequently, the nature of the gathered data affects the SEU as sensitive data is valued more highly.

True to its name, SEU is highly subjective. As no outcome of an action can be predicted with certainty, the calculated situational privacy depends on the customers subjective probability of the anticipated outcome occurring (Gouthier et al., 2021; Kokolakis, 2015). In his study, Acquisti (2004) investigates the reasons behind the proposed privacy paradox, and claims that one of the reasons that individuals struggle to make logical judgements concerning data privacy is due to our society becoming more information oriented. The way data is viewed as currency has blurred the distinction between private and public further complicating the privacy calculus in digital environments. He suggests an equation to calculate a customer's reasoning behind the privacy calculus outcome, but admits that multiple parameters, such as incomplete information, bounded rationality, and psychological distortions such as cognitive biases, will alter every individual's decision-making process. Bounded rationality signifies the "limitations facing a human decision maker – limitations of both knowledge and computational capacity" (Kokolakis, 2015).

As a single model of rational privacy behaviour is unrealistic due to the complexities of human cognition, more attention should be focused on models of self-control bias and immediate gratification to be able to study consumers' privacy related decision making. As most individuals are affected by cognitive limitations, we tend to resort to heuristics such as affect and perceived trust when carrying out privacy calculus (Gouthier et al., 2021; Acquisti, 2004; Kokolakis, 2015). For example, online retailers who clearly and visibly disclose privacy policies attract more purchases (Kokolakis, 2015). This can be assumed to be closely related with perceptions of trust, as low privacy concerns can strengthen the feeling of trust towards an organization (Chen et al., 2022). Transparency regarding the technical details of how personalization is implemented in digital systems also provide the customer more insights on how their data is utilized.

2.5 Marketing Automation

Marketing automation refers to the data-driven creation of marketing content that utilizes automatic or semi-automatic processes for continuous optimization (Järvinen & Taiminen, 2016). It is depicted in Figure 1 as subset of e-commerce personalization, as personalization in e-commerce often takes the form of automated and personalized marketing messages. The reliance on automated marketing practices can be seen as merely an approach to marketing operations or as a holistic approach to business, aimed to influence organizational processes, business strategies and culture (Mero et al., 2020). It is a common marketing strategy in e-commerce along with personalization, and often deemed as a prerequisite to successful marketing. Personalization and marketing automation are often used interchangeably in business lingo, as data-driven personalization is an automated process. However, this paper differentiates personalization as a sub strategy of marketing automation. This establishes a distinction between what personalization aims to achieve, which is to deliver relevant content to customers, and how marketing automation makes this possible by harnessing the power of data through a variety of tools and technologies.

The process of marketing automation comprises of the calibration phase, triggering, and evaluation (Heimbach et al., 2015). The calibration phase refers to analysing the current situation, setting objectives, and sourcing data to be utilized in the automation process. The collection and storage of customer data used in marketing automation is often handled by the company's CRM (Customer Relations Management) system. The CRM is a key operational tool which creates value through the management of customer relations, enabling organizations to foster long-term relationships with customers. However, modern marketing automation exceeds the affordances of CRMs, as it aims to utilize data from multiple sources to create dynamic marketing communication (Heimbach et al., 2015). Apart from the CRM, companies can follow user behaviours with analytics software tools such as Google Analytics (Järvinen & Taiminen, 2016). The data collected can be either qualitative, quantitative, or descriptive (Lark, 2022). Qualitative data can be gathered from interactions between the business and the customer, whereas quantitative data is usually collected through questionnaires. Descriptive data provides more context for the qualitative information, and can include information on the customers lifestyle, such as hobbies or marital status for instance.

To create triggers, predefined marketing actions are mapped to historical or current user data and as well as user actions. Insights are drawn from customer segments created based on various data points such as demographics, user actions on website, or response to direct communication (Heimbach et al., 2015). Different user segments can then be paired with rules for prompting automated marketing actions. For example, a customer of the age of 18 to 25 can be approached with "back-to-school"- themed marketing campaigns in the beginning of Autumn, to target their possible return to university. The amount and quality of data can however make a difference in determining whether the customer is enrolled in university.

The consequences of the marketing actions are evaluated, and some marketing actions may be considered advantageous, leading to the creation of new sets of automation rules (Heimbach et al., 2015). The analytical frameworks utilized in this evaluation process can be divided into four categories: descriptive, diagnostic, predictive and prescriptive analytics (Insight Software, 2021). Descriptive analytics sheds light on past trends, whereas diagnostic analytics seek a reason to why it happened. Predictive analytics on the other hand aims to predict what will happen in the future and prescriptive analytics aspires to find ways to affect these future goals. All these frameworks provide insights into trends and customer behaviours and can be further used for optimizing already existing automated marketing content and delivery, either through AI and machine learning or monitoring conducted by the company.

2.6 Recommender systems

Illustrated in Figure 1 as a subsection of marketing automation, recommender systems are algorithms commonly used in e-commerce that aim to suggest relevant content to users and have an effect of guiding a user in a personalized way to discover interesting or useful content (Burke, 2002). The use of recommender systems is valuable in online environments, in which the amount of content is larger than what a user can efficiently process. They are data-driven, and thus require background data of the content and users along with input data, which is generated dynamically through user interactions, as well as an algorithm that connects these two. As the field of data science advances, more techniques for recommender systems surface. Two of the main recommender systems techniques are content based and collaborative filtering based (Fan & Poole, 2006; Burke, 2002; Rocca, 2019), but other simpler systems are also utilized such as demographic recommenders.

According to Burke, “In a content-based system, the objects of interest are defined by their associated features” (Burke, 2002). The descriptions are explicit and are a representation of the characteristics of the items to be recommended. This descriptive data is stored in a database, and in the context of e-commerce will usually be structured, such as product attributes like price or the category they belong to. Content-based recommendation systems rely on analysing this data to identify what would be of interest to the user, based on the similarity of the users previously preferred items (Pazzani & Billsus, 2007; Rocca, 2019). Depending on whether recommendations are based on user or product features, a model will be created based on the chosen variable making the method either user-centred or product-centred (Rocca, 2019).

The method being either user or item centred means that recommendations are based on the appeal of an item to an individual user, or the appeal of an item to many users. In the user-centred method, the model assigned to the user is therefore based on item characteristics, and vice versa. Hybrid models are also possible. The model ultimately outputs predictions for classifiers or ratings for content, making content-based filtering a predictive analytics tool by predicting whether the content will be of interest to the customer according to the filtering output (Rocca, 2019). These classifiers and ratings are subsequently used to produce recommendations that are shown to the customer.

Another common predictive analytics tool is collaborative filtering (Fan & Poole, 2006). In this method, user-content interactions are stored in the user-item interaction matrix, from which predictions are drawn on the similarity between both users and content (Rocca, 2019). User and item profiles are continuously augmented through time and increased interactions (Burke, 2002), making mature collaborative filtering systems more efficient than new ones. However, as Koren states, explicit user profiles or domain knowledge are not required for collaborative filtering techniques, thus avoiding the necessity for collecting extensive amounts of personal data (Koren, 2010). It should be stated, however, that rather descriptive data on user behaviour can be uncovered using past interactions only.

Collaborative filtering can be done without assuming a model of interaction, meaning that in this case the recommended content is solely based on the user-item interactions of similar users (Burke, 2002). This discipline is called the *neighbourhood approach* (Koren, 2010), as it seeks to locate the closest "neighbours" of a user profile based on the similarity of their past activities or other commonalities, and the preferences of these neighbours are then used to create recommendations. This approach can also be handled based on item-item resemblance, in which case the preference of a user for a specific item is considered and thereof recommendations are drawn according to the similarity of the previously preferred items.

Alternatively, models can be drawn for user-item interaction data (e.g., makeup is more commonly purchased by women, toys are purchased by parents) to create a latent model to drive recommendations (Rocca, 2019). Unlike the models used in content-based filtering, the data used in latent factor models is not explicit nor is it based solely on the user or item. Rather, it is automatically generated from implicit or explicit user feedback to create comparable and expressive relationships between users and content (Koren, 2010). Model-based recommenders use a variety of machine learning technologies to create the models used for collaborative filtering, using data from the interaction matrix (Burke, 2002; Rocca, 2019).

Demographic filtering is yet another type of recommender system, widely used due to its simplicity and to address the cold-start problem of the previously mentioned recommendation systems, which Safoury & Salah describe as the lack of data when a new user joins the system and no recommendations can be made (Safoury & Salah, 2013). This system uses demographic data such as location, age, and gender to assign recommendation rules for aggregates of people, if users within the same demographic have similar preferences. As Burke points out, demographic filtering does not suffer from the cold start problem but can run into issues when attempting to gather demographic data, as some users may find it invasive to request this type of information for marketing purposes (Burke, 2002). However, when such demographic data is available e.g., through frequent buyer profiles, demographic filtering can be relatively quick to set up as a more rudimentary recommender technique or used alongside collaborative or content-based techniques to create a hybrid approach.

3 Benchmarks From Industry

The following chapters will discuss the successes, pitfalls, and strategies of three e-commerce organizations that have implemented personalization in their retail business strategy. The companies were chosen to highlight various aspects of successful implementation or unforeseen consequences and the benchmark cases portray various methods and outcomes of deploying personalization technologies and strategies in an e-commerce environment.

3.1 Target

Target is the seventh largest retailer in the United States and boasts with an annual revenue of 104.62 billion dollars in 2021 (Soltes, 2022). The retail giant offers a wide range of consumer goods and provide in-store and online shopping. Target has taken the convergence of IT and retail seriously. It has been collecting user data earnestly for decades and has distinguished itself in being a forerunner in utilizing data analytics to provide its customers with personalized shopping experiences (Lipka, 2014). However, the drive to create cross-selling opportunities and increase sales by data-driven personalization resulted in a public outcry about the state of big data operations in the field of retail.

A New York Times article written by Charles Duhigg told the story of an outraged father of a 16-year-old Target customer who arrived at a Target store to complain about his child receiving coupons for various baby items, usually marketed for pregnant people (Duhigg, How Companies Learn Your Secrets, 2012). It turned out, that Target had previously invested in hiring Andrew Pole, a skilled data-analyst who created a “pregnancy-prediction model” which could deduct an individual to be pregnant due to previously purchased items. This segmentation would then be used to target personalized email advertisements to that individual (Duhigg, How Companies Learn Your Secrets, 2012). The pregnancy-related digital marketing content was therefore not an accident, but an example of Poles prediction model working as it should – the father is said to have called in and admitted that his daughter was in fact pregnant.

The account is purely anecdotal and does not provide scientific proof of the accuracy of the algorithm, as no data is available on whether the 16-year-old was even targeted by the prediction model or how many pregnant people the algorithm succeeds in distinguishing. However, Target was getting results with their investment in predictive data analytics. The company grew their revenue from $44 billion to $65 billion in the 7 years after hiring Pole in 2002, and in 2005 it’s president declared a “heightened focus on items and categories that appeal to specific guest segments such as mom and baby” (Duhigg, The Power of Habit: Why We Do What We Do, and How to Change, 2012). This suggests that the segmentation and marketing tactics around personalization, however controversial, were successful in creating value to both company and customer.

Furthermore, the personalization utilized by Target had another goal – to not come off as repellent or intrusive. To achieve this, they would slide coupons for baby products in with deals on other mundane consumer items as to not create suspicion (Duhigg, How Companies Learn Your Secrets, 2012). The customers already had purchasing habits for other items that they needed, and now all Target had to accomplish was to piggyback on the pre-existing purchasing habits of the customer with the new and personalized content.

Research suggests that individuals are more susceptible to changing consuming habits and brand preferences when undergoing significant life changes (Andreasen, 1984). These can entail a lifestyle change, increased income, aging, and of course, pregnancy, which Target specifically focused on. Studies propose that habit formation starts with a cue for the brain to perform a routine. The completion of this routine then provides the person with a reward, which promotes the attractiveness of the specific habit (Graybiel, 2008). This process creates associations between the cue, routine and reward and is often "contextually bound and relatively automatic" (Balleine & O'Doherty, 2010, s. 51). Thus, getting in on the automated purchasing habit that has previously been formed allowed Target to create cross-selling opportunities with personalized content scattered in, and this action was the most effective when applied at a time when the customer was the most receptive to advertising and changing their purchasing behaviours – at the cusp of big life changes.

In conclusion, Target was able to effectively deploy personalization both due to extensive data collection and state-of-the-art data analytics tools and expertise, but also by concentrating on behavioural sciences to figure out the most optimal moments to present the customers with marketing content. The creation and implementation of the prediction models was a large endeavour, on which Target consciously allotted time and budget to. Moreover, the anecdote of the coupon mishap illustrates how dynamic algorithm-generated content can potentially lead to undesirable outcomes.

3.2 Best Buy

Best Buy is a multinational consumer electronics retailer, which also offers in-store repair services for electronics (Fortune, 2022). Best Buy's marketing strategy is highly human-centred, and Neil Saunders, the managing director of GlobalData Retail mentioned that Best Buy operates on the presumption that it can use technology to enrich people's lives (Bhattarai, 2018). This human-centred approach has been a driving force for their success in creating strong customer relations based on personalized services. Best Buy is renowned for its ability to create and foster strong customer relationships and creating a sense of exclusivity across multiple touchpoints. This success has been noted with a high placement in the annual Retail Personalization Index by Sailthru, where Best Buy claimed fourth place among 500 participants (2022).

During the pandemic, when many US retailers were experiencing revenue loss, Best Buy was thriving despite not being regarded as a retailer of “essential” goods (Walton, 2020). Moreover, the goods they do offer are also sold elsewhere. To combat these short-comings and to set them apart from competitors, they shifted their strategy to focus on frictionless, personalized, multichannel customer service and service design (Grill-Goodman, 2022).

Best Buys human-centred approach to retail is driven by customer data. The collected data is leveraged to bridge together all customer touchpoints, as the company’s CEO states: “There are a myriad of touchpoints — online, offline, mobile. All the experiences need to stitch together. It has to be a frictionless experience no matter how they interact. Build your omnichannel experiences around your customers' expectations” (Keenan, 2022). The streamlining of shopping processes between online and offline is also powered by data analysis, as Best Buy’s ongoing customer research frequently validates the hypothesis that purchases begin online and are carried out in brick-and-mortar stores (Minkow, 2022). There is ongoing on how exactly this channel-hopping carried out in each customer journey, but it provides the company with a valuable notion of making the traditional and valued customer experience easily accessible also through digital mediums, resulting in seamless online and offline shopping experiences for each individual.

To create a great personalized customer experience, Best Buy relies on their strengths, and has created an ecosystem encompassing data-analysis, brick-and-mortar stores, and various digital platforms. The technical support and advice previously provided in-store by specialists have been made accessible also to online shoppers through chat or phone, and a subscription for unlimited technical support has been introduced (Bhattarai, 2018). They have implemented “Virtual Stores”, in which customers can interact with knowledgeable staff and get demos of products as well as personal advice on products (Grill-Goodman, 2022). This illustrates how digital personalization and one-on-one personal services can be amalgamated.

Personalization is also a key feature in their mobile app, which enables the customer to gain rewards by checking in at their local store. This gives the customer an incentive to use the localization features, which can in turn be used to collect valuable data on how customers navigate the store, giving Best Buy a great leverage in collecting customer data to gain insights. Furthermore, Best Buy utilizes location data to personalize their advertising with the help of local inventory ads which showcase relevant products to customers based on their availability in nearby stores and providing them with a shop pickup link. The effectiveness is compelling – these local inventory ads drove over 1 million shop visits according to Google (Google, 2016). The app also features personalized recommendations, AR preview and store maps to find products in-store, all of which turn online shopping into a tangible experience (Best Buy, 2022).

3.3 Anonymous retail conglomerate

The third case study was conducted as an open-ended interview with an UX designer from a large retail organization which has taken a huge digital leap in the last few years and has integrated personalization well into their brand image. The organization has so far implemented personalization in their mobile app and website in the form of search results based on purchase behaviour, targeted offers, newsletters, and personalized recipe recommendations based on the products that they offer. Currently the team of designers working on personalization entails five employees.

The interviewee spoke on behalf of the UX team responsible for the organization's personalization efforts. The role of the UX designers is focused on identifying potential customer touchpoints which would benefit from personalization aspects, as well as conducting user research during various steps of the implementation process. This includes both usability testing in a controlled environment as well as running A/B tests in production and sending out questionnaires to customers pertaining to the experimental group to report how the personalization was received. According to the interviewee, business metrics are intrinsically tied to the testing process and the A/B testing focuses on examining the effects of personalization primarily on KPI's such as click-through-rate and conversion to decipher the viability of the feature and is supported by the user questionnaires.

As stated by the interviewee, the UX teams' approach to implementing personalization was to offer customers with more interesting content which positively impacts the customer experience. The interviewee did not highlight any particular problem statement for the design process but noted that as their personalization features require the user to be logged in, a large part of building personalization features revolves around finding incentives for customers to register to the organization's digital platform and services. For instance, the retailer's website and mobile application will prompt the user to register by describing how this will benefit them by providing access to tailored content. Reputedly, the customers interviewed about the personalization features did not express anxieties over ceding data, as they have gained a thorough understanding of the benefits provided by the organization in exchange for their information, a novel phenomenon in today's e-tail environment.

Newsletters sent out to customers containing personalized product recommendations and offers are not handled by the UX team, affirms the interviewee. This area is managed by marketing teams and the interviewee admitted to not being fully aware of their practices and operations. They however state the importance of the relationship between marketing proceedings and UX when it comes to designing and testing personalization features successfully. Nevertheless, marketing segments are not usually accounted for by the UX team in the design process but are utilized in testing situations.

4 Methodology

The following chapter will discuss the methodological approaches utilized in the study, by first providing a descriptive analysis of the study's adopted methods. The SWOT analysis was chosen as a practical choice for approaching RQ1: "What are the opportunities and pitfalls of implementing data-driven personalized marketing content?", due to its qualitative nature, as it allows for more detailed and descriptive conclusions to be drawn. The SWOT analysis facilitates the design and implementation of the MVP that is to be A/B tested to answer RQ2. The methodological process is presented in Figure 5.

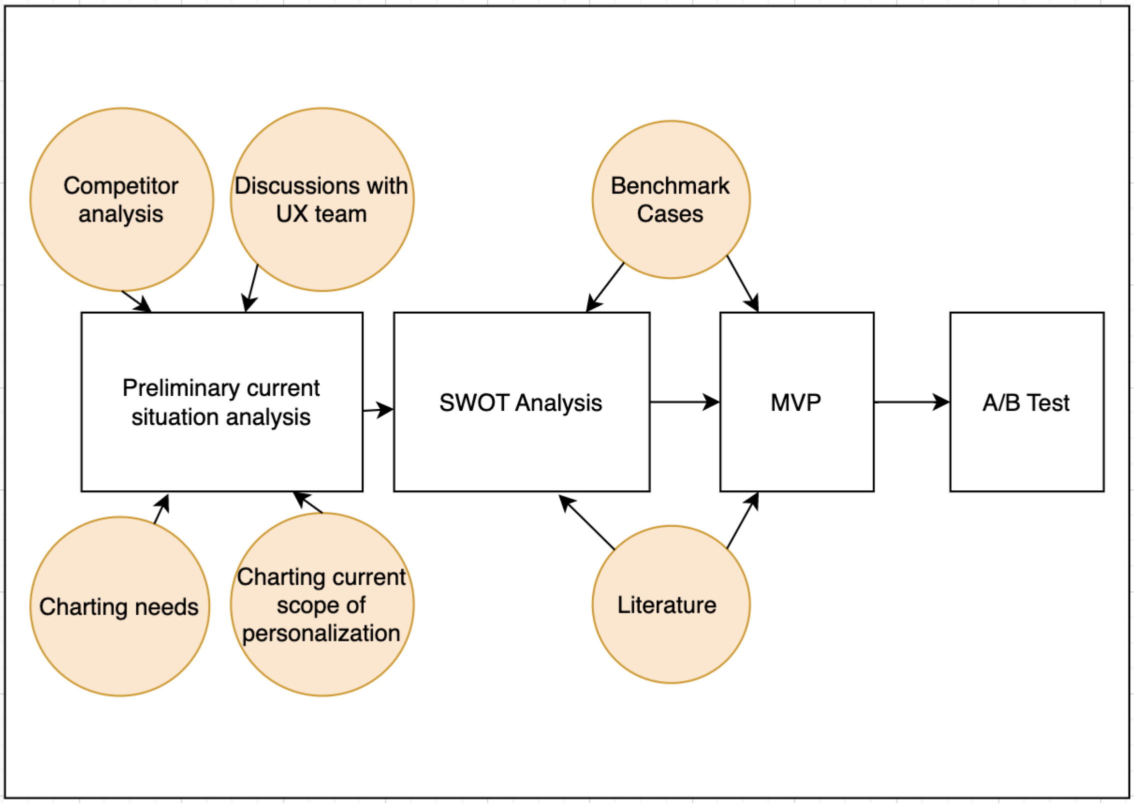


Figure 5. Process.

4.1 SWOT Analysis

A SWOT analysis is a tool commonly used in the business world to map the *strengths*, *weaknesses*, *opportunities,* and *threats* of a company in the context of a specific venture before embarking on it. The main objective of the analysis is to provide the company with an exhaustive outlook on the factors that are involved in creating a business decision (Schooley, 2022). According to Namugeniya et al., a SWOT analysis entails identifying the internal and external factors that affect the company and its business performance in a specific scenario (2019). The internal factors to be considered in the analysis are the *strengths* and *weaknesses* components of the matrix, meaning those attributes of an organization that may either hinder or facilitate reaching the specified objective. *Threats* and *opportunities*, on the other hand, represent the external aspects that could influence achieving the goal (Namugenyia et al., 2019).

When conducting a SWOT analysis, its four components are placed in a matrix to attain a well-defined view of how the internal and external opportunities and pitfalls relate to each other. These relationships can potentially lead to the discovery of advantageous insights, such as previously overlooked blind spots or opportunities that had formerly gone unnoticed. The SWOT analysis can be accompanied by a further thematic analysis to dig deeper into the findings. The newly realized comprehensions should be accounted for when the organization moves forward with the business venture and constructs an action plan based on the SWOT analysis. Helms and Nixon point out that the plan of action strives to preserve and leverage the organization's core competences, while defending against exposure to core problems (Helms & Nixon, 2010).

The SWOT analysis was conducted by the author and aimed to test the preliminary viability of the implementation of automated and personalized marketing content. It builds on the previously conducted research, benchmark cases as well as the authors knowledge of the organisation. Prior to the creation of the SWOT analysis, preliminary current situation analysis was conducted by charting current needs, UX and business goals and conducting competitor analysis (see Figure 5). The points made refer to both the overall strengths, weaknesses, opportunities, and threats of personalization as well as those of automated personalization in the context of Power Finland. The SWOT matrix is accompanied by a further elucidation of the discovered notions and the themes uncovered in the process.

4.2 MVP

A Minimum Viable Product (MVP) is an early iteration of an idea, technology, or feature to test on early adopters (Muzyka, 2022). It can be used to test the for example the market demand of something that a company plans to implement. An MVP contains the most integral functionality of the planned feature, and it is tested early in the product development stage. This allows for quick testing and companies can decide early whether the feature is viable for further development. Creating MVP's is a core element of lean methodology, in which feedback is gathered quickly and continually by rigorous streamlining of processes and iterative product development (planview, 13).

Testing a feature using an MVP can take many forms but will always entail delivering a feature to the public with the core functionality which gets the point of the feature across and getting feedback on it. The feedback can be in the form of customer reactions, or the MVP can be used to collect analytics data, both of which give valuable information on the features market reception and whether more extensive product development should be carried out. For the purpose of this study, the implemented MVP aims to generate a scalable system for a personalization feature with a minimal initial investment to pave way for further development in case the feature is successful.

To test the effect of an automated personalization feature in the form of an MVP, a sophisticated recommendation algorithm is not necessary for the scope of this study. In concurrence with the findings of the research which state that personalization is especially useful in boosting the desirability of loyalty programs, the implemented personalization should draw data from a logged in user's profile to widen the range of functionalities the customer has access to when joining Power's loyalty program. This is also due to the ease of data extraction as well as to ensure that a user has consented to their data being utilized for marketing purposes. Moreover, as the research on privacy issues suggests, disclosure of marketing intentions facilitates the building of trust and can make consumers more accepting towards their data being used for marketing purposes.

It should be noted that the MVP implemented in the study aims to discover whether personalization makes a difference in a specific context and use case. In this case the feature is product recommendations, which are related to the "*Promotions*" personalization feature mentioned in the literature review. To provide more value to MyPower users and to test the effect of personalization based on explicitly declared preferences, MyPower users' preferences are used to create a personalized product recommendation carousel.

A registered and logged in customer has access to their loyalty programme profile page, MyPower, which contains settings for the users' preferences concerning communication, the accumulation of Power Bonus, and consent for personalization. Moreover, it presents the customer with an opportunity to select out of the following six themes of interest: Beauty and Wellbeing (*Kauneus ja hyvinvointi*), Entertainment (*Viihde*), Food and Cosiness (*Ruoanlaitto ja mukavuus*), Gaming (*Pelaaminen*), Health and Fitness (*Terveys ja urheilu*), and Smart Home (*Älykoti*).

This data is saved into Voyado CRM to be used by marketing employees and developers. Currently, this data is used solely for showing a logged in customer text articles that contain tags corresponding to their declared interests. To use the same interest preferences for product recommendations, a mapping of interests to products is implemented, similar to the existing one of interests to articles. For the scope of the thesis, changing the structure of the product or category data models to include tags is not feasible, and mapping individual products would similarly be overly labour-intensive. However, product data models include service categories which allow for direct mapping of items to customer interests.

Figure 6. Product carousel on Power's Website.

4.3 A/B Testing

A/B testing is a data collection method that seeks to gather comparative data on the performance of two alternatives of a variant in a testing scenario. A/B tests are a common testing strategy in user experience research as well as digital marketing and have become standard practice in the field of marketing automation. The advantage of controlled experiments, according to Kohavi et al., are that they allow “establishing a causal relationship with high probability” (Kohavi & Longbotham, 2016). This implies that hypotheses can be scientifically tested to provide an answer to whether variable X will improve certain key metrics, compared to variable Y.

Despite, or perhaps due to, its simplicity, A/B testing is a powerful testing strategy. It provides the organization accuracy and confidence in the test results with minimal effort once the A/B testing environment has been set up. Furthermore, being able to test small entities separately allows for implementing changes in the UI or marketing messages without running the risk of adverse side-effects (Bojinov et al., 2020; Koren, 2010). A common practice in several large user-facing IT-firms is to have multiple A/B tests running continuously parallel to generate data on which alternative layouts, components or interactions are better received by the users.

The A/B test that is conducted in the study to measure the MVP’s performance is run with Google Optimize which has been used by Power Finland in previous A/B testing scenarios. The A/B test measures the difference in conversion rate, revenue, and bounces between the two variants, the original product recommendation carousel and the interest-based one. Whereas a higher conversion rate and revenue are desired outcomes of an A/B test, an increased bounce rate is not. Conversion and revenue increasing with the B variant (MVP), would further support the strengths and opportunities found in the SWOT analysis, but an increase in bounce rate indicates that the tested variant does not serve to retain customers on the site or increase their engagement. The statistical validity of the A/B results is tested with the non-parametric Mann-Whitney U test. A non-parametric test was chosen as normality could not be assumed with the KPI data. The Mann-Whitney U test was chosen as it can determine if two groups are significantly different, therefore being appropriate for A/B test result analysis.

The Optimize experiment is targeted at 50% of the visitors of the website, who are logged in, are club members, have consented for personalization and have declared one or more interests on their MyPower profile page. To determine whether a customer meets these criteria, a boolean type data layer variable is made available in Google Tag Manager. Data layer variables allow fetching data from the application to be used in various tasks related to analytics. If a session meets the requirements to be included in the experiment, Google Optimize triggers a script changing the recommendation variants to be interest based rather than the original version. Due to possible promotional campaigns being run by different countries where Power operates, the experiment is conducted only on the Finnish site to simplify communications. As the sample size of customers who have saved their interests and given consent for personalization may be quite small, the experiment is run for a month to gather sufficient data to obtain a reliable result.

5 Findings

The following chapter relays the results of the SWOT analysis as well as the A/B test conducted with the implemented MVP.

5.1 SWOT Analysis

Strengths	Weaknesses
- MyPower loyalty program for prior trust bulding and access to customer data. - Voyado CRM for efficiently managing customer data. - Google Analytics already in use for customer research purposes. - Umbraco CMS has packages available for marketing automation. - Manual personalization already implemented. - Strong brand visibility. - Upcoming mobile application opens more avenues for personalization and data collection. - Due to the nature of the company many of the customers are tech savvy, which could imply more appreciation towards personalization.	- At this point no resources allocated for automated personalization. - Limited communication between development/UX team and marketing. - Brand trust may be affected by problem areas such as delivery difficulties and congested customer service.
Opportunities	**Threats**
- Increased revenue. - Increased customer satisfaction. - Potential to make up for some of the organization's weak points. - Automatic personalization would let marketing allocate time to other tasks. - Increased number of MyPower registrations. - Improved brand image. - More opportunities and benefits for customers.	- Can lead to disappointment or switching to competitor if personal needs cannot be catered to. - If privacy tradeoff is not sufficiently beneficial to customer, they may not want to give access to their data. - Apprehensions about data privacy - Potentially perceived as invasive. - Costs if done through third party. - Oversimplifying customer segments if only relying on data.

	- Nudging customers to rely on heuristics and fast decision making can skew data on actual customer preferences and trends

5.1.1 Strengths

Power Finland's strengths regarding the implementation of automated personalization revolve mainly around the pre-existing infrastructure utilized for data handling. The main systems in use are Umbraco as a content management system, Google Analytics for data analytics on website use and Voyado CRM for customer relations. Umbraco is mainly used by marketing teams to create campaigns and product recommendations for the website. Personalization is also therefore carried out in Umbraco, albeit manually. Integration of the robust data provided by Voyado or Google Analytics would therefore offer a viable base to build automated personalization upon. Furthermore, in addition to customer data found on multiple platforms, a mobile application is under development which can provide even more opportunities for data collection and marketing automation.

Further strengths lie in what Power Finland provides to its customers. MyPower is a frequent buyer program providing customers with benefits such as special offers and a portal to keep up with their purchase history. Customers are prompted to register to MyPower during various stages of their customer journey, with examples of the benefits a customer can expect upon registering. Stathopoulou & Balabanis discovered in their study that the right benefits provided by loyalty programs increase trust, and this was especially the case within hedonistic benefits. For example, trust in the loyalty program is increased when the "retailer uses the customer's personal information to personalize hedonic benefits", such as personalized birthday messages and offers (Stathopoulou & Balabanis, 2016). This suggests a symbiotic relationship between a strong loyalty program and personalization.

5.1.2 Weaknesses

Automated personalization can free up resources once up and running, however its implementation requires workforce dedicated to the project and enough time. As of now, the IT team of Power Finland is small, and no roles are dedicated to either the design of personalization or implementation. As seen from the conducted case studies, the successful design and implementation of automated personalization requires effort and often organizational changes, as moving from manual to automated personalization can imply a paradigm shift in the organization encompassing both marketing and IT departments.

Another weakness lies in the geographical location of Power Finland's employees. Various operational teams reside and work across multiple cities in the Nordics, and seamless cooperation face-to-face is challenging, although there has recently been increasingly more communication across teams. The iterative nature of designing personalization according to continuously changing user needs and evaluating whether automation works as intended is best monitored by designers, developers, and marketing employees.

Trust in the organization offering personalization is a frequently surfacing factor in literature on personalization. Successful interactions with the organization and brand image can increase trust, but dissatisfaction with the offered services can worsen a customer's perception on the brand and lead to distrust, which may influence them to not want to cede their personal data to the company. Power Finland has had issues with extended delivery times and congested customer service, which can negatively affect trust as well as its value proposition, which, as stated earlier, is a prerequisite for implementing successful marketing personalization.

5.1.3 Opportunities

The literature review conducted in this paper boasts with a wide array of benefits associated with personalized marketing automation. These benefits consist of increased revenue, customer satisfaction and the boosted effectiveness of capital spent on marketing. Effective personalization has the potential of leading into a clearer brand image, and thus can make up for certain shortcomings of the organization. Internally, having a working automated marketing personalization system would also free resources to tackle some of the pain points in the company.

For individual personalization as opposed to collective personalization, such as that based on demographics, access to customer data is crucial. The most robust data can be retrieved from customers' MyPower profiles, and personalization can act as a motivator for registering for an account. The value proposition of the Power's loyalty program would therefore benefit from personalization, making it more appealing for customers to join. Moreover, capturing a customer's attention by addressing their self-schema can incentivize them to spend more time on the site and positively influence their perception of the company, or the recommended product. Addressing the self-schema also augments the persuasiveness of the marketing message, which can have a positive impact on the intent to purchase.

5.1.4 Threats

Many of the threats considered in the SWOT analysis revolve around data privacy. Some customers may be apprehensive about having their data used for marketing purposes, and personalized marketing messages could potentially be viewed as being invasive. Another reason apart from potential apprehensions towards data-driven marketing using personal data, the collection of personal information can be inhibited by a privacy trade-off that does not offer adequate benefits to justify providing data access. If, however, a customer decides to cede access to their data but later deem the benefits of this trade-off suboptimal, they may experience disappointment. These notions relate to the perceived trust and attitudes towards the system and are crucial points to consider during design and implementation.

When conducting marketing personalization, the aim is to uncover hidden trends and preferences. However, a possible threat when relying on fast decision making and extreme persuasiveness is that the data on actual customer preferences can be skewed by effective marketing, and the company's business goals. Additionally, solely relying on mainly unmonitored data can lead to the oversimplification of customer segments, as there is no humane input in the data-analysis. This can especially be an issue with more rudimentary recommendation systems without sophisticated machine learning models.

5.2 MVP

The web store already has product recommendations implemented in the form of carousels and lists, using a third-party service. These are based on previously viewed items and currently popular products, as seen in Figure 6. For uniformity, the preference-based personalized product recommendations were chosen to follow a similar format. The MVP therefore will also be implemented with the same carousel UI as the existing product recommendation carousels. However, the MVP will use user preferences to populate the new version of the carousel, making it personalized for each user. Most of the recommendations are placed on the landing page of the webstore, excluding a few recommendation carousels placed on product or category pages, making the landing page also a reasonable location for the interest-based recommendations.

The implementation of the product recommendations was carried out by initially mapping the product service categories to the six interest categories in an SQL database. These mappings were then used to fetch the applicable service categories for logged in users who have saved their interests in MyPower if the interests could be fetched from Voyado. Products were then queried with Elasticsearch (Elasticearch, 2023) to be accessed in the front-end of the website through an API endpoint and were fetched according to their relevance and stock count. The order of the queried products was random, but it did consider those products with a higher desirability score to be returned first.

The products were then rendered to the user in an image carousel on the front page. The carousels are Angular components comprised of product tiles. The tiles contain an image as well as information of the product and can be clicked for the customer to be routed to the product page. The carousel component rendering the recommendations takes an input determining which variant of recommendations is currently used, original or interest based. The component also tracks product list impressions to Google Analytics to obtain more additional data on the reach and impact of the new variant of recommendations along with the A/B test.

5.3 A/B Test

The analytics data collected by the Google Optimize was exported in three parts: data for transactions, revenue, and bounces. The data was exported in .csv format and included columns for the date index of each day the experiment was ran, amount of daily experiment sessions for both variants, and the number of transactions, bounces, or amount of revenue for each day, for both variants. When exported to an Excel worksheet, the rates per session of transactions and bounces were calculated by dividing the number of daily events by daily sessions. Likewise, the revenue per session was calculated by dividing the amount of daily revenue by the number of daily sessions.

Data on the mean of the daily changes in KPI's as well as the standard error and deviation were calculated and then plotted to a graph. The bar charts visualize the marginal difference between the two variants regarding bounce rate (Figure 7), transaction rate (Figure 8) and daily revenue (Figure 9). As seen from the overlap of the standard deviation in each graph, the data was too dispersed to be statistically significant. To further solidify the findings, a Mann-Whitney U test was performed on each set of data to evaluate whether bounce rate per session, transaction rate per session or revenue per session differed by variant. The results indicated that there was no significant difference between the bounce rate *[U = 325.00, p = .137]*, transaction rate *[U = 374.00, p = .453]* or revenue *[U = 406.00, p = .821]* of the original product recommendations and the interest-based product recommendations. Therefore, the null hypothesis is rejected as the data shows no difference presented in key KPI's when comparing the original variant to the interest-based product carousel.

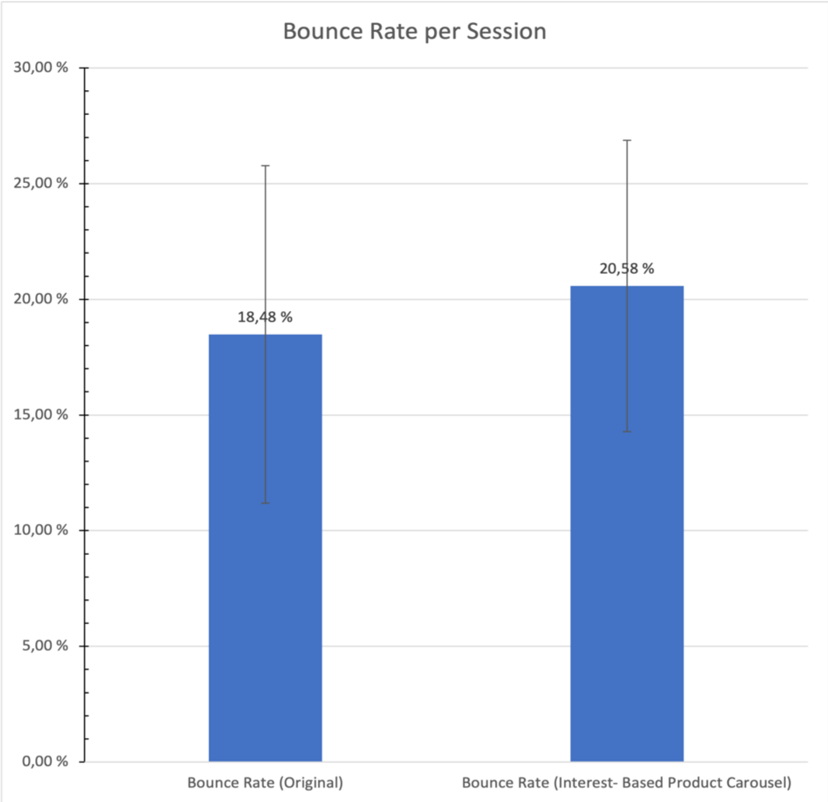


Figure 7. Bounce rate per session with standard deviation.

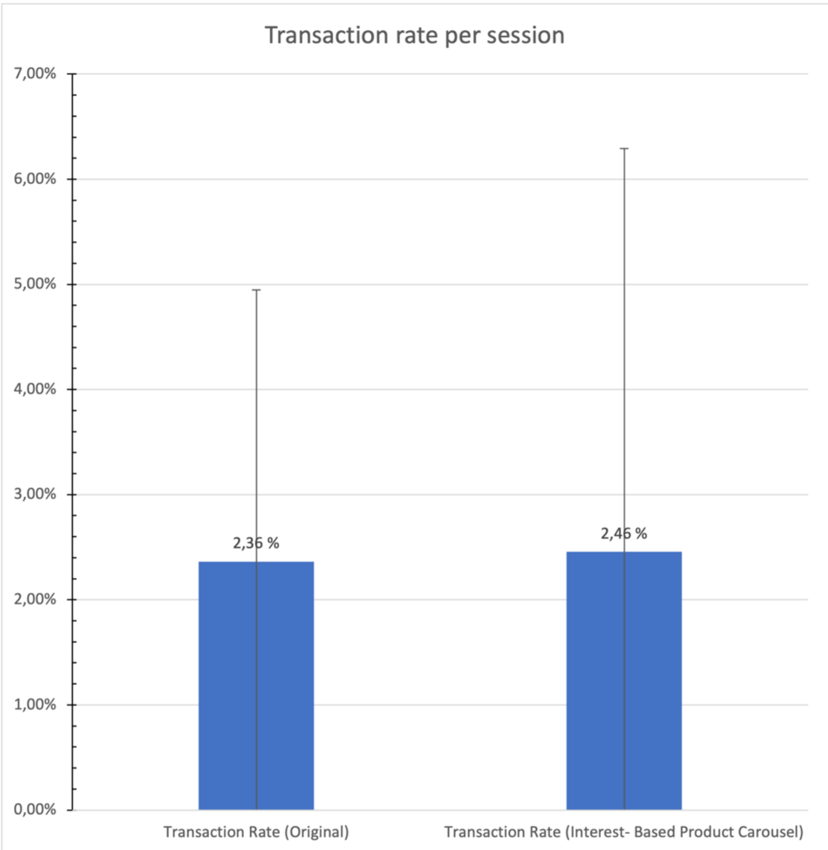


Figure 8. Transaction rate per session with standard deviation.

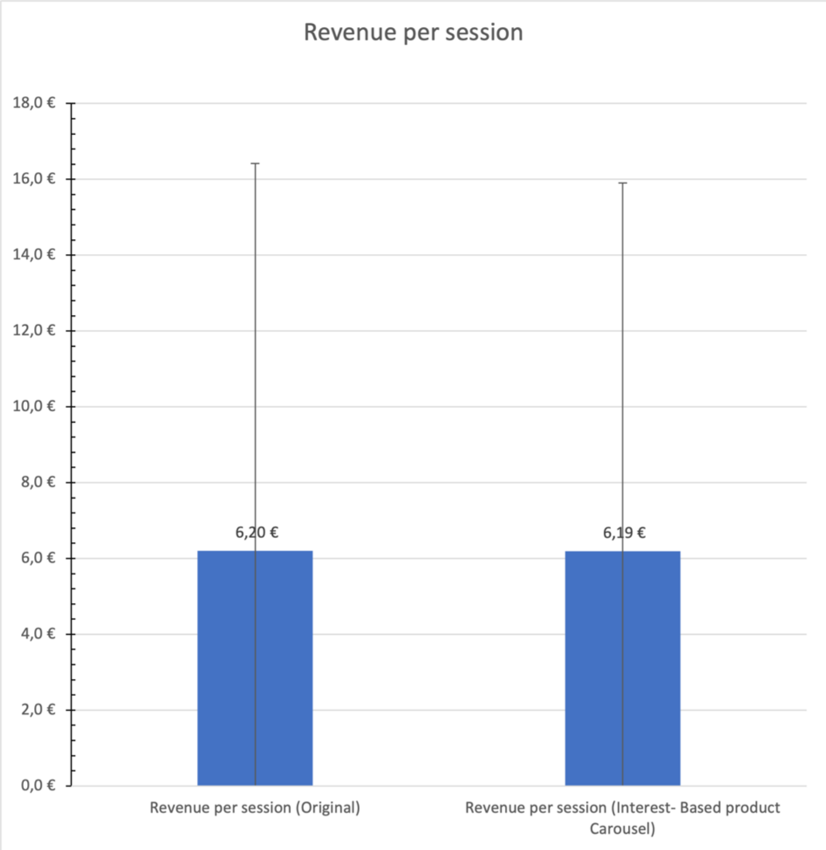


Figure 9. Revenue per session with standard deviation.

6 Discussion and Conclusion

The final chapter of the thesis provides discussion on the outcome of the study and offers insight into some of its shortcomings as well as potential future work along with concluding words.

6.1 Results in retrospect

Overall, the findings support that automated personalization is a worthy effort for Power Finland to delve in further. The answer to the first research question, "*What are the opportunities and threats of implementing automated personalized marketing content in the context of e-commerce?*" can be answered with the findings of the cross-examination of the results of the SWOT analysis. Firstly, the subject of MyPower was prevalent in various dimensions of the matrix. The development of personalization should thus be intertwined with the development of MyPower, as they mutually support each other. The loyalty program supported by personalization addressing the customer on a personal level, either individually or based on belonging to a demographic, can help foster long lasting customer relationships, as addressing the persona of the customer creates the impression of a unique experience. This is an expectation of consumers when interacting with digital services, and aids in boosting customer satisfaction.

Another prevalent theme is data privacy, which is an often-discussed threat based on a multitude of resources on personalization due to the possibility of customers refusing to let their data be used for marketing purposes. However, although there may exist a subset of customers that do hold these apprehensions, personalization has become so commonplace that customers are usually well versed on the trade-off proposed by personalization. The studies presented in this paper indicate a necessity for developers and designers to be cognizant of the possibility that customer data can be misused and the effect this has on customers but also show a necessity for organizations to introduce personalization in their business plans. Similarly, the conducted expert interview with a UX designer focused on personalization revealed that data privacy was not a major issue in their organization, suggesting at similar attitudes towards it among the customer base of other digital services.

Resource allocation is likewise a theme considered in the weaknesses section, for as of now the resources allocated to personalization are limited. Building and maintaining personalization requires effort from various teams including marketing, UX and development to create personalized features which produce desired results. There should be consensus on the magnitude of the personalization in terms of the company's business plan and how well it is integrated into marketing strategies. If addressed, however, successfully integrating personalization into all company operations bears the opportunity of strengthening brand image and automated personalization especially can support other business operations by letting some teams allocate more of their time on certain problem areas in the company.

The second research question, "*Are automated personalized product recommendations more effective than Power's current product recommendations?*" is answered with the results of the conducted A/B test. The A/B test showed no significant difference between the original product recommendations and the interest-based ones in terms of KPI's, therefore not supporting automated, personalized recommendations being more effective than Powers current ones. Although not an encouraging outcome, the finding helps unveil some problems regarding the state of product recommendations as it is.

Upon further examination of data observed by Google Analytics, it was noted that the reach of both variants at their current placement do not receive much interaction in the form of views or swipes. The A/B test therefore does not provide us with enough robust data to clearly differentiate between the effectiveness of the variants if the overall impressions are minimal. The low number of interactions on the original variant indicate that product recommendations do not presently work as intended due to either delivery or placement. Moreover, the text currently accompanying any product recommendations does not address the customer directly, and all variants of the recommendation carousels are not on the forefront of the page, but the customer must scroll down to view them. This neglects the personalization aspect and does not evoke a feeling in the customer of having a personal relationship with the brand, which is central theme in developing successful personalization in e-commerce.

6.2 Future work

As has been stated, there are multiple factors at play when implementing personalization in an e-commerce context, and solely concentrating on one aspect of it is unable to deliver much useful data. The conducted SWOT analysis deals with data-driven personalization as a whole, whereas the A/B test focuses on only one type of personalization, in which explicitly stated preferences are used to create data-driven product recommendations. A further look into the SWOT analysis could be done by concentrating on a specific type of personalization, as the way data-driven personalization is implemented can have big differences in the outcome. This way the A/B test could also be targeted at a specific type of personalization, or two variants of it and would be more suited to support the findings of the SWOT analysis. The focus of the SWOT analysis could be on technology, interface, or different channels of personalized content, for example.

As stated in the research and benchmark cases, the endeavour of implementing successful automated personalization is a cross-disciplinary one, as more emphasis should be put on how personalisation is delivered to the customer and how it fits with the overall brand strategy. Clarification of expectations regarding personalization and product recommendations is therefore in order when moving forward. The lack of clicks on the interest-based recommendation carousel might indicate that it displays irrelevant products to the customer, but as the original variant does not receive much interaction either, there is a possibility that before allocating resources to the technical implementation, reaching the customer in a consistent and efficient manner should be considered a priority. Self-referencing messages, captivating visual stimuli, placement, and the amount of emphasis of personalization in Power's brand promise are all potential variables to consider when moving forward.

Going forward, a similar A/B test could be conducted where the product carousel is in a clearly visible location on the front page. Similarly, A/B testing a personalization feature would yield more accurate results if tested on a website feature that has been proven to be effective, thus reducing the number of confounding variables. The A/B test could also be modified to measure the amount of clicks each variant gets to determine whether automatic recommendations based on the customers own interests do a better job at capturing their attention than generic recommendations. Finally, this study did not consider the rising number of mobile users in e-commerce. It would be thus beneficial to examine the implications of implementing personalization in a mobile context.

6.3 Concluding words

To conclude, personalization in e-commerce has become a staple part of a successful business's strategy over the years. However, for personalization to be successful, it requires multidisciplinary efforts to guarantee benefits for both customer and organization. It should be able to reach the customer and effectively address them while fostering an environment of trust. The creation of trust is also quintessential for data acquisition, and the use of personalized marketing content should be balanced enough to not come across as intrusive. However, self-referential messaging is proven to be effective in getting messages across and making them memorable. Creating the right balance in personalized content is an iterative process, from both a design-based and a technical perspective. The technical implementation of personalization can be approached from various angles, such as fully automated collaborative filtering, or personalization based on user preferences, both of which have their own implications when it comes to design.

The themes which were uncovered in the SWOT analysis indicated that in Power's case, personalization presents the company an opportunity to enhance their loyalty program MyPower. Therefore, personalization should not be implemented as a purely technical feature, but it should be woven into the further development of MyPower. In the A/B experiment conducted, there was no significant difference in key KPI's between the two variants, which indicated that there was no tangible improvement in KPI's when interest-based recommendations were introduced to test the viability of personalization. However, the uncovered issues in the product recommendation carousels provide valuable insight into some potential future focal points in marketing and UX. The delivery method of marketing messages on Power's website requires improvement and should be primarily tackled to ensure the efficiency of personalized content. Although the A/B test did not provide support for implementing personalization in the specific A/B test scenario, the overall research backs up the importance in introducing personalization into business.

7 Bibliography

Accenture Interactive. (2018). *MAKING IT PERSONAL Why brands must move from communication to conversation for greater personalization.* Accenture Interactive.

Accenture. (2020). *WE, THE POST-DIGITAL PEOPLE Can your enterprise survive the tech-clash?* Accenture.

Acquisti, A. (2004). Privacy in Electronic Commerce and the Economics of Immediate Gratification. *ACM*.

Andreasen, A. R. (1984). Life Status Changes and Changes in Consumer Preferences and Satisfaction. *Journal of Consumer Research*, 784-794.

APA Dictionary of Psychology. (2022, October 9). Retrieved from American Psychology Association: https://dictionary.apa.org/self-schema

Ariker, M., Heller, J., Diaz, A., & Perrey, J. (2015, November 23). *How Marketers Can Personalize at Scale.* Retrieved from Harvard Business Review: https://hbr.org/2015/11/how-marketers-can-personalize-at-scale

Babet, A. (2020). *Utilization of personalization in marketing automation and email marketing.* Retrieved from MA thesis School of Business and Management: https://lutpub.lut.fi/handle/10024/161404

Ball, A. D., Coelho, P. S., & Vilares, M. J. (2003). *Service Personalization and Loyalty.* Retrieved from Marketing Department Faculty Publications.: https://digitalcommons.unl.edu/marketingfacpub/13

Balleine, B. W., & O'Doherty, J. P. (2010). Human and Rodent Homologies in Action Control: Corticostriatal Determinants of Goal-Directed and Habitual Action. *Neuropsychopharmacology Reviews*, 48,69.

Best Buy. (2022, October 23). *Put a 24/7 shopping companion on your phone.* . Retrieved from Best Buy: https://www.bestbuy.com/site/misc/mobile-app/pcmcat208500050016.c?id=pcmcat208500050016

Bhattarai, A. (2018, May 24). *The Washington Post*. Retrieved from Best Buy has figured out what its customers want: Personalized advice: https://www.washingtonpost.com/news/business/wp/2018/05/24/best-buy-has-figured-out-what-its-customers-want-personalized-advice/

Bojinov, I., Saint-Jacques, G., & Tingley, M. (2020). *Avoid the Pitfalls of A/B Testing.* Retrieved from Harvard Business Review: https://hbr.org/2020/03/avoid-the-pitfalls-of-a-b-testing?ab=at_art_art_1x4_s02

Burke, R. (2002). Hybrid Recommender Systems: Survey and Experiments1. *User Modelinga nd User-Adapted Interaction*, 331-370.

Carrascal, J., Riederer, C., Erramilli, V., Cherubini, M., & de Oliveira, R. (2013). Your browsing behavior for a big mac: economics of personal information online. *WWW '13: Proceedings of the 22nd international conference on World Wide Web*, (pp. 189–200).

Chen, X., Sun, J., & Liu, H. (2022). Balancing web personalization and consumer privacy concerns: Mechanisms of consumer trust and reactance. *Journal of Consumer Behaviour*, 572–582.

Debevec, K., & Romeo, J. B. (1992). Self-Referent Processing in Perceptions of Verbal and Visual Commercial Information. *Journal of Consumer Psychology*, 83-102.

Duhigg, C. (2012, February 16). *How Companies Learn Your Secrets.* Retrieved from The New york Times Magazine: https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

Duhigg, C. (2012). *The Power of Habit: Why We Do What We Do, and How to Change.* Random House.

Dzulfikara, M. F., Purwandari, B., Sensuse, D. I., Lusa, J. S., Solichah, I., Prima, P., & Wilarso, I. (2018). Personalization Features on Business-to-Consumer E-Commerce: Review and Future Directions. *2018 4th IEEE International Conference on Information Management*, (pp. 220-224).

Elasticearch. (2023, April 13). *What is Elasticsearch?* Retrieved from Elasticsearch: https://www.elastic.co/what-is/elasticsearch

Fan, H., & Poole, M. S. (2006). What Is Personalization? Perspectives on the Design and Implementation of Personalization in Information Systems. *Journal of Organizational Computing and Electronic Commerce*, 181.

Fortune. (2022, August 3). *Fortune*. Retrieved from Best Buy: https://fortune.com/company/best-buy/

Gefen, D., & Straud, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services. *The International Journal of Management Science*, 407-424.

Google. (2016, August). *Think With Google*. Retrieved from Best Buy Draws Customers In-Store With Mobile : https://www.thinkwithgoogle.com/intl/en-cee/marketing-strategies/app-and-mobile/best-buy-draws-customers-instore/

Gouthier, M. H., Nennstiel, C., Kern, N., & Wendel , L. (2021). The more the better? Data disclosure between the conflicting priorities of privacy concerns, information sensitivity and personalization in e-commerce. *Journal of Business Research*, 178-189.

Graybiel, A. M. (2008). Habits, rituals, and the evaluative brain . *Annu Rev Neurosci.*, 359-387.

Gregg, B., Kalaoui, H., Maynes, J., & Schuler, G. (2016, November 18). *Marketing's Holy Grail: Digital personalization at scale.* Retrieved from MacKinsey Digital: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/marketings-holy-grail-digital-personalization-at-scale

Grill-Goodman, J. (2022, March 7). *RIS News*. Retrieved from 3 Keys to Best Buy's Omnichannel Performance: https://risnews.com/3-keys-best-buys-omnichannel-performance

Heimbach, I., Kostyra, D. S., & Hinz, O. (2015). Marketing Automation. *Bus Inf Syst Eng*, 129 - 133. Retrieved from AIS Electronic Library (AISeL): https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1328&context=bise

Helms, M. M., & Nixon, J. (2010). Exploring SWOT analysis – where are we now? *Journal of Strategy and Management*, 215-251.

Ho, S. Y. (2006). The Attraction of Internet Personalization to Web Users. *Electronic Markets*, pp. 41-42.

Hracs, B. J., & Webster, J. (2021). From selling songs to engineering experiences: exploring the competitive strategies of music streaming platforms. *Journal of Cultural Economy*, 246-248.

Huber, O., & Seiser, G. (2001). Accounting and convincing: The effect of two types of justification on the decision process. *Journal of Behavioral Decision Making*, 69-85.

Insight Software. (2021, February 17). *Comparing Descriptive, Predictive, Prescriptive, and Diagnostic Analytics*. Retrieved from Insight Software: https://insightsoftware.com/blog/comparing-descriptive-predictive-prescriptive-and-diagnostic-analytics/

Instone, K. (2004). An Information Architecture Perspective on Personalization. *Designing Personalized User Experiences in eCommerce*, 75-93.

Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management*, 164-175.

Keenan, J. (2022, January 17). *Total Retail*. Retrieved from 5 Trends Best Buy is Targeting for 2022 Success: https://www.mytotalretail.com/article/5-trends-best-buy-is-targeting-for-2022-success/

Kisielius, J., & Sternthal, B. (1984). Detecting and explaining vividness effects in attitudinal judgments. *Journal of Marketing Research*, 54.

Kohavi, R., & Longbotham, R. (2016). Online Controlled Experiments and A/B Testing. In C. Sammut, & G. Webb, *Encyclopedia of Machine Learning and Data Mining.* New York: Springer Science+Business Media New York.

Kokolakis, S. (2015, 10 July). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & Security*, p. 2015.

Koren, Y. (2010). Factor in the Neighbors: Scalable and Accurate Collaborative Filtering. *ACM Transactions on Knowledge Discovery from Data*.

Lark, J. (2022, November 16). *Collecting Data for Hyper-Personalized Marketing*. Retrieved from Fleximize: https://fleximize.com/articles/014664/data-for-hyper-personalized-marketing

Lipka, M. (2014, January 23). *Reuters*. Retrieved from What Target knows about you : https://www.reuters.com/article/us-target-breach-datamining-idUSBREA0M1JM20140123

Mero, J., Tarkiainen, A., & Tobon, J. (2020). Effectual and causal reasoning in the adoption of marketing automation. *Industrial Marketing Management*, 212-222.

Minkow, M. (2022, March 31). *RetailWire*. Retrieved from Best Buy and others find great customer experiences start with data insights: https://retailwire.com/discussion/best-buy-and-others-find-great-customer-experiences-start-with-data-insights/

Muzyka, B. (2022, June 30). *PoC vs Prototype vs MVP: What's the difference? How to choose?* Retrieved from TechMagic: https://www.techmagic.co/blog/poc-vs-prototype-vs-mvp/#:~:text=A%20proof%20of%20concept%2C%20prototype,the%20market%20receives%20your%20idea.

Namugenyia, C., Nimmagaddab, S. L., & Reinersc, T. (2019). Design of a SWOT Analysis Model and its Evaluation in Diverse Digital Business Ecosystem Contexts. *23rd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems* (pp. 1145–1154). Procedia Computer Science.

Norberg, P. A., Horne, D. R., & Horne, D. A. (2007). The Privacy Paradox: Personal Information Disclosure Intentions versus Behaviors. *The Journal of Consumer Affairs*, 100-126.

O'Keefe, D. J. (2002). *Persuasion: Theory and research.* Thousand Oaks: Sage Publications.

Oberoi, P., Patel, C., & Haon, C. (2017). Technology sourcing for website personalization and social media marketing: A study of e-retailing industry. *Journal of Business Research*, 10-23.

Ordanini, A., & Parasuraman, A. (2011). Service Innovation Viewed Through a Service-Dominant Logic Lens: A Conceptual Framework and Empirical Analysis. *Journal of Service Research*, 3-23.

Park, J. (2003, August). *Consumer attitudes toward personalization features and intention to purchase online.* Retrieved from University of Tennessee: https://trace.tennessee.edu/utk_graddiss/5168

Parkes, C. (2001, 01 12). *Enterprise Systems Journal.* Retrieved from The Power of Personalization Web technologies get personalized to increase profits: https://esj.com/articles/2001/12/01/the-power-of-personalization.aspx?m=1

Pazzani, M. J., & Billsus, D. (2007). Content-Based Recommendation Systems . *The Adaptive Web*, 325-341.

planview. (13, April 2023). *LEAN METHODOLOGY*. Retrieved from planview: https://www.planview.com/resources/articles/lean-methodology/#:~:text=Lean%20Methodology%20Summary,improvement%20and%20respect%20for%20people.

Ranaweera, C., & Prabhu, J. (2003). On the relative importance of customer satisfaction and trust as determinants of customer retention and positive word of mouth. *Journal of Targeting, Measurement and Analysis for Marketing* , 82–90.

Riecken, D. (2000). Introduction: Personalized Views of Personalization. *COMMUNICATIONS OF THE ACM*, 1.

Rocca, B. (2019, June 3). *Towards Data Science*. Retrieved from Introduction to Recommender Systems: https://towardsdatascience.com/introduction-to-recommender-systems-6c66cf15ada

Safoury, L., & Salah, A. (2013). Exploiting User Demographic Attributes for Solving Cold-Start Problem in Recommender System. *Lecture Notes on Software Engineering*.

Sailthru. (13, April 2023). *2022 retail personalization index*. Retrieved from planview: https://www.sailthru.com/personalization-index/

Schooley, S. (2022, August 05). *SWOT Analysis: What It Is and When to Use It.* Retrieved from Business News Daily: https://www.businessnewsdaily.com/4245-swot-analysis.html

Soltes, F. (2022, July 6). *National Retail Federation*. Retrieved from 2022 Top 100 Retailers : https://nrf.com/blog/2022-top-100-retailers

Stathopoulou, A., & Balabanis, G. (2016). The effects of loyalty programs on customer satisfaction, trust, and loyalty toward high- and low-end fashion retailers. *Journal of Business Research*, 5801-5808.

Tam, K. Y. (2006). UNDERSTANDING THE IMPACT OF WEB PERSONALIZATION ON USER INFORMATION PROCESSING AND DECISION OUTCOMES. *MIS Quarterly*, 865-890.

Tintarev, N., & Masthoff, J. (2011). Designing and Evaluating Explanations for Recommender Systems. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor, *Recommender Systems Handbook* (pp. 479-507). Springer Science+Business Media.

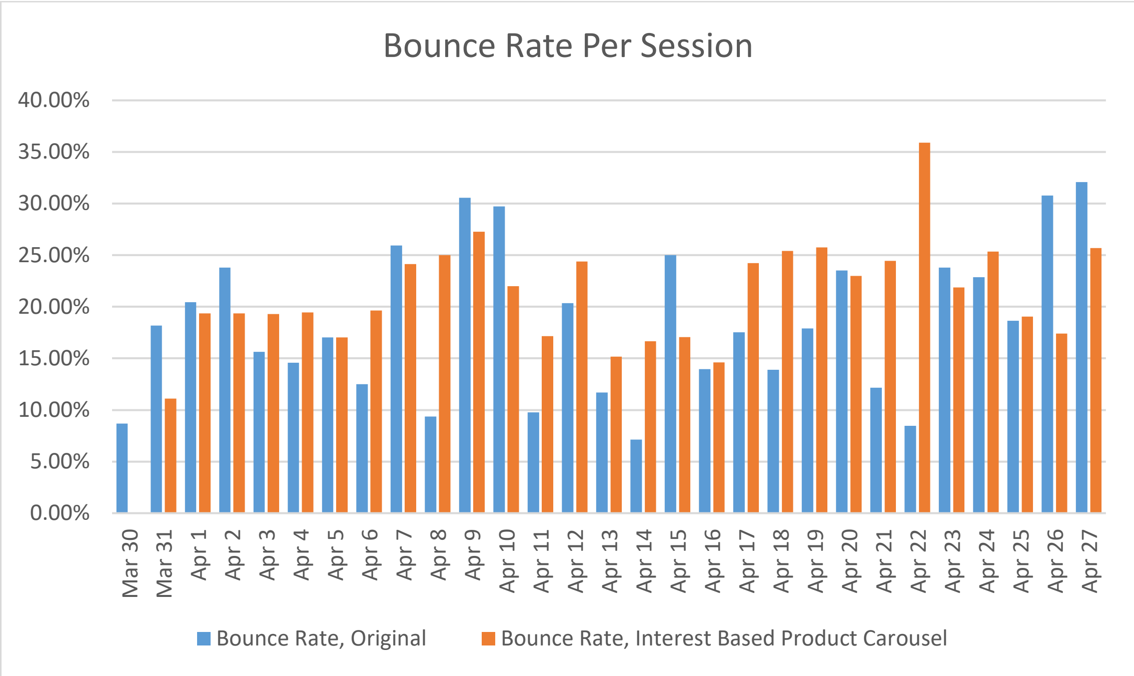
Vesanen, J. (2007). What is personalization? A conceptual framework. *European Journal Of Marketing*, 409-418.

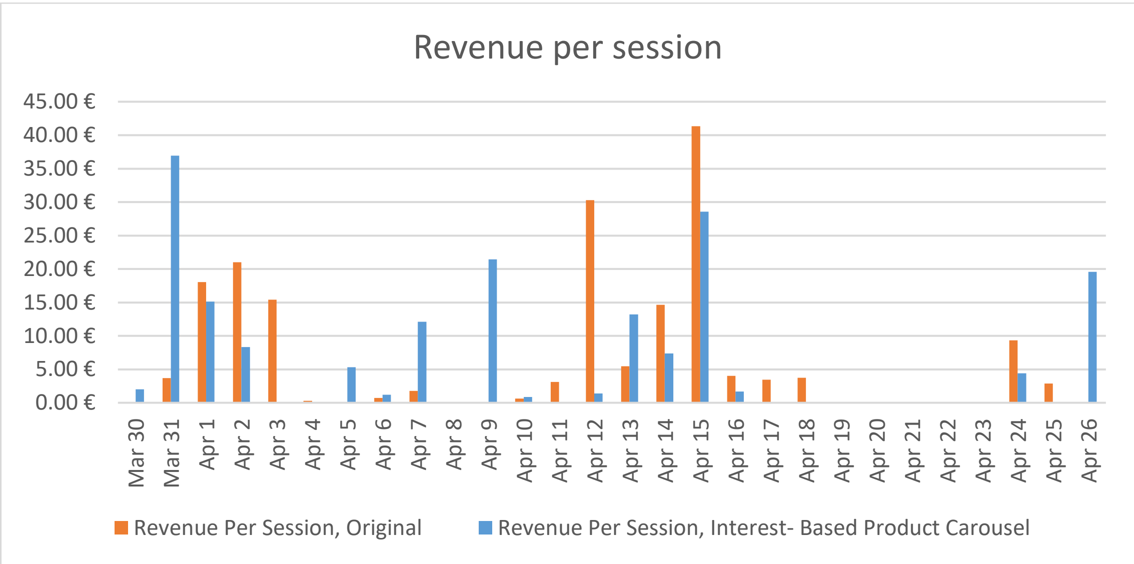
Walton, C. (2020, December 15). *How Best Buy Used Its Retail Smarts To Stand Out In 2020—And Set Itself Up For Success In Shopping's New World*. Retrieved from Forbes: https://www.forbes.com/sites/christopherwalton/2020/12/15/best-buy-is-the-smartest-retailer-of-2020/?sh=57c8273548f9

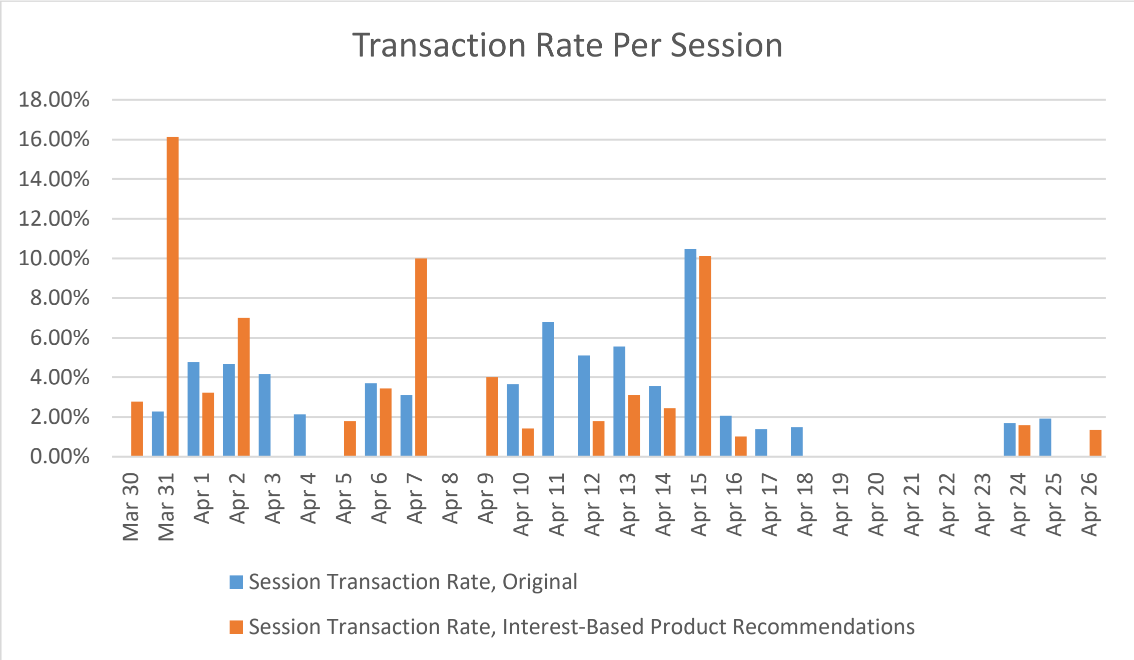
Wheeler, S. C., Petty, R. E., & Bizer, G. Y. (2005). Self-Schema Matching and Attitude Change: Situational and Dispositional Determinants of Message Elaboration. *Journal Of Consumer Research*, 787-897.

Zhu, H., Ou, C. X., Heuvel, W. v., & Liub, H. (2017). Privacy calculus and its utility for personalization services in e-commerce: An analysis of consumer decision-making. *Information & Management*, 427-437.

Appendix A: A/B Test Results






Transaction Rate Per Session
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Mar 30
Mar 31
Apr 1
Apr 2
Apr 3
Apr 4
Apr 5
Apr 6
Apr 7
Apr 8
Apr 9
Apr 10
Apr 11
Apr 12
Apr 13
Apr 14
Apr 15
Apr 16
Apr 17
Apr 18
Apr 19
Apr 20
Apr 21
Apr 22
Apr 23
Apr 24
Apr 25
Apr 26
Session Transaction Rate, Original
Session Transaction Rate, Interest-Based Product Recommendations